Agroforest Syst (2025) 99:104
https://doi.org/10.1007/s10457-025-01197-6

Role of exposure in adoption and intensity of tree planting practices among smallholder households in Rwanda

Hilda Kegode · Damien Jourdain · Tesfaye Woldeyohanes · Karl Hughes · Selma Tuemumunu Karuaihe

Received: 13 August 2024 / Accepted: 7 April 2025

Abstract Agroforestry, widely promoted across Sub-Saharan Africa to restore degraded landscapes and improve livelihoods, has the potential to positively impact Sustainable Development Goals (SDG), specifically SDG15 (life on land) and contribute towards the achievement of SDG2 (food security) and other SDGs. However, despite substantial investment in agroforestry programs, evidence of program effectiveness in enhancing adoption is inadequate. This paper employed the augmented inverse probability weighting method to analyze the impact of exposure to agroforestry practices on the adoption and intensity of tree planting using panel household data from Eastern Rwanda. The findings show that exposure increased the probability of adoption by 7% ($p=0.03$). A higher probability of adoption (15%, $p=0.01$) was observed in households that were exposed both before and after the baseline period, suggesting cumulative effects of exposure over time. Exposure modestly enhanced the diversity of trees and the number of trees in cropping fields, but farmers tended to adopt more exotic than indigenous species. A higher probability of adoption and higher tree numbers were observed when male household members were exposed, and seedling provision enhanced tree numbers and species among adopters. Our findings underscore the need for continuous engagement of farmers and targeted gender-sensitive interventions. We also recommend a more structured approach to training and information dissemination, and a focus seedling availability and a suitable policy environment.

Keywords Agroforestry programs · Tree-planting adoption · Augmented inverse probability weighting · Rwanda

H. Kegode (✉) · T. Woldeyohanes · K. Hughes
Impact Assessment and Acceleration Unit, World Agroforestry (ICRAF), CIFOR-ICRAF, UN Avenue, Gigiri, Nairobi, Kenya
e-mail: h.kegode@cifor-icraf.org; u20487623@tuks.co.za

H. Kegode · D. Jourdain · S. T. Karuaihe
Department of Agricultural Economics, Extension and Rural Development, Center for Environmental Economics and Policy in Africa (CEEPA), University of Pretoria, Private Bag X20, Hatfield 0028, South Africa

D. Jourdain
CIRAD, UMR G-EAU, Hatfield 0028, South Africa

D. Jourdain
G-EAU, Univ Montpellier, AgroParisTech, BRGM, CIRAD, INRAE, Institut Agro, IRD, Montpellier, France

Introduction

Many communities in Low- and Middle-Income Countries (LMICs), such as Rwanda, depend on natural resources to produce food and sustain their livelihoods. However, environmental degradation poses a major challenge especially to rural smallholder households. Approximately 1.5 billion people are affected by

Published online: 13 May 2025

land degradation globally (UNCCD 2014), with the highest percentage in Sub-Saharan Africa (SSA) (Nkonya et al. 2016; Wawire et al. 2021). Hillbrand et al. (2017) estimated that 65% of agricultural land, 30% of pastureland and 20% of forests in Africa are degraded. This causes low agricultural productivity, threatens food security and leads to poverty especially among rural smallholder farmers (Coulibaly et al. 2017; Hillbrand et al. 2017; Pratiwi and Suzuki 2020; Cyamweshi et al. 2023; Ngango et al. 2023). These negative effects are aggravated by climate variability, unsustainable agricultural practices and population pressure (Asrat and Simane 2017; Ngango et al. 2023; Veste et al. 2024; Zaca et al. 2023). To date, environmental degradation continues to elicit discussion globally, with increased focus and investment particularly in LMICs. Various solutions have been proposed to address such degradation, some of which include low tillage agriculture, conservation farming, using physical technologies to control soil erosion and agroforestry.

Agroforestry, the integration of trees or woody perennials in farming systems, has been widely promoted and considered an effective land restoration strategy (Mwase et al. 2015; Coulibaly et al. 2017; Hillbrand et al. 2017; Cornelius and Miccolis 2018; Pantera et al. 2021; Wawire et al. 2021; Muthee et al. 2022; Ntawuruhunga et al. 2023; Veste et al. 2024). By providing ecosystem services, such as climate regulation, soil erosion control, and soil moisture and fertility retention, agroforestry is one of the ways through which landscapes can be restored (Hillbrand et al. 2017; Buyinza et al. 2020; Wawire et al. 2021; Ngango et al. 2023). Additionally, it supplies products such as fuelwood, fruits, livestock fodder and herbs for household consumption and sale (Hillbrand et al. 2017). Agroforestry technologies, practices and activities, including tree planting, grafting, farmer-managed natural regeneration (FMNR), nursery establishment and management and tree care have been promoted across Africa, directly supporting SDG15 by reducing natural habitat depletion and SDG2, by fostering food security to eliminate hunger.

Despite the potential of agroforestry to improve landscapes and livelihoods, its effectiveness depends on household adoption and sustained practice of promoted technologies and activities (Kulindwa and Ahlgren 2021; Ngango et al. 2023). Various studies exist on agroforestry adoption and practice in SSA. Kpoviwanou et al. (2024) found that 54% of agroforestry adoption literature in Africa focused on factors affecting adoption, and 27% assessed trends and challenges in agroforestry adoption. About 12% investigated environmental and socio-economic benefits of adoption while the remainder examined motivation for adoption and intensification of agroforestry. In Eastern Africa, Buyinza et al. (2020) analyzed how psychological factors affect farmer agroforestry adoption decisions in Uganda, Syano et al. (2022) studied factors influencing agroforestry adoption in Kenya, and Jha et al. (2021) investigated factors affecting adoption of agroforestry by smallholders in Tanzania. However, these studies mainly focus on factors affecting the adoption decision and not necessarily the intensity of agroforestry practices. The closest examples are Ngango et al. (2023) who analyzed adoption decisions, intensity of adoption and challenges of agroforestry adoption in Rwanda and Kulindwa (2016) who specifically analyzed household tree planting behaviour in Tanzania. However, both Ngango et al. (2023) and Kulindwa (2016) used cross-sectional data, hence ignored the time aspect in adoption. The former study analyzed adopters and non-adopters of agroforestry without controlling for selection bias. Both studies also used different variables as indicators of intensity, with the former using the area under agroforestry practice and the latter using only the number of trees planted.

While previous studies contribute significantly to agroforestry literature, very few rigorously assessed the effectiveness of agroforestry programs in encouraging adoption of practices in SSA (Baylis et al. 2016; Cameron et al. 2016; Hughes et al. 2020; Miller et al. 2020; Castle et al. 2021; Malan et al. 2024). A systematic review by Castle et al. (2021) found that most studies on agroforestry program impact relied on non-experimental data and overlooked methodological risks, like selection bias, thus neglecting the non-random participation of farmers or households in the programs. This could impact outcomes and affect conclusions (Leßmeister et al. 2018; Castle et al. 2021; Malan et al. 2024), for example, benefits may be overestimated if selection bias and confounders are not accounted for. Another research gap relates to inadequate research on information barriers which have been identified as potential impediments to adoption among farmers (Kpoviwanou et al. 2024; Mugizi 2025;

Kiyani et al. 2017). Many agroforestry programs aim to increase human capital, by providing information, knowledge and skills to farmers through trainings and extension programs. However, this factor has not received much attention in the literature (Danquah and Amankwah-Amoah 2017; Wossen et al. 2017; Rudolf et al. 2020), resulting in the dearth of credible empirical evidence required to design or improve programs. Additionally, agroforestry adoption studies such as Zaca et al. (2023) only analyzed access to extension service as a binary factor affecting adoption but did not explore how heterogenous parameters of exposure such as the gender of the persons exposed, the topics of exposure and the sources of exposure influenced adoption. This obscures critical pathways that may be important for optimizing programs.

This study attempts to address the gaps highlighted above in the following ways: first, using a quasi-experimental approach—the augmented inverse probability weighting (AIPW) method. AIPW controls potential selection bias and provides more credible results than regression models (Kurz 2022). Second, using multiple indicators besides adoption to evaluate the intensity of tree planting provides richer information that can inform future agroforestry program decisions and actions. The intensity of agroforestry practice is estimated by six indicators including tree species diversity and number of trees found around homes and in cropping fields. Furthermore, we unpack the treatment variable to estimate the impact of specific aspects including the gender of household members exposed, the various sources that provided exposure and the topics covered on adoption and agroforestry practice using AIPW. This approach acknowledges the heterogeneity in exposure and allows more specific recommendations to be made. The use of panel data also captures the dynamism in the adoption indicators. Finally, the paper provides important insights about impact of agroforestry programs and contributes to the agroforestry impact evaluation literature.

The rest of this paper proceeds as follows: Sect. "Study area and context, sampling, and data" describes the study area, sample, data, and descriptive statistics. Sect. "Theoretical and empirical approaches" discusses the theoretical and empirical models employed. Results are presented in Sect. "Results" and discussed in Sect. "Discussion". Sect. "Conclusion and recommendations" concludes and makes some recommendations.

Study area and context, sampling, and data

Study area

Rwanda is a small country in Eastern Africa. It has different physical features including rivers, lakes, forests and a hilly terrain, which makes it susceptible to soil erosion (Ngango et al. 2023). With 503 persons/km^2, the country is densely populated (NISR 2023), placing a huge demand on natural resources. Farm sizes are small and households engage in subsistence rain-fed agriculture as the main economic activity (NISR 2023); cultivating crops throughout the year. This makes land fallowing impossible and leads to degradation (Mugizi 2025; Veste et al. 2024). This study was conducted in four out of seven districts in the Eastern province: Bugesera, Gatsibo, Kayonza and Nyagatare (Fig. 1).

These districts were specifically selected because they had been targeted by a land restoration program, Regreening Africa (RA), which was implemented from September 2017 to February 2023, by World Vision Rwanda in areas that had experienced high levels of land degradation. The program was part of a larger program implemented in eight African countries.[1]

Although the four districts have similar environmental conditions like climate and soils, Gatsibo and Kayonza districts are more forested than other districts in the province (MinEnv 2019). The villages in this study, however, are not within the highly forested zones, hence their selection for land restoration interventions. Some parts of Gatsibo district are high altitude, supporting the cultivation of crops such as coffee, while parts of Kayonza district border the Akagera National Park and exhibit drier conditions compared to other parts of the district. Land degradation, population pressure and climate variability in the province underscore the need for land restoration and strategic resource management. While Rwanda experiences tropical climate with annual rainfall averaging over 1000 mm, the Eastern province

[1] The program was implemented in Ethiopia, Ghana, Kenya, Mali, Niger, Rwanda, Senegal, and Somalia by five international development organizations including: World Vision International, Catholic Relief Services, CARE International, Oxfam International and SAHEL-Eco. Information on the program can be found on the website: https://regreeningafrica.org/

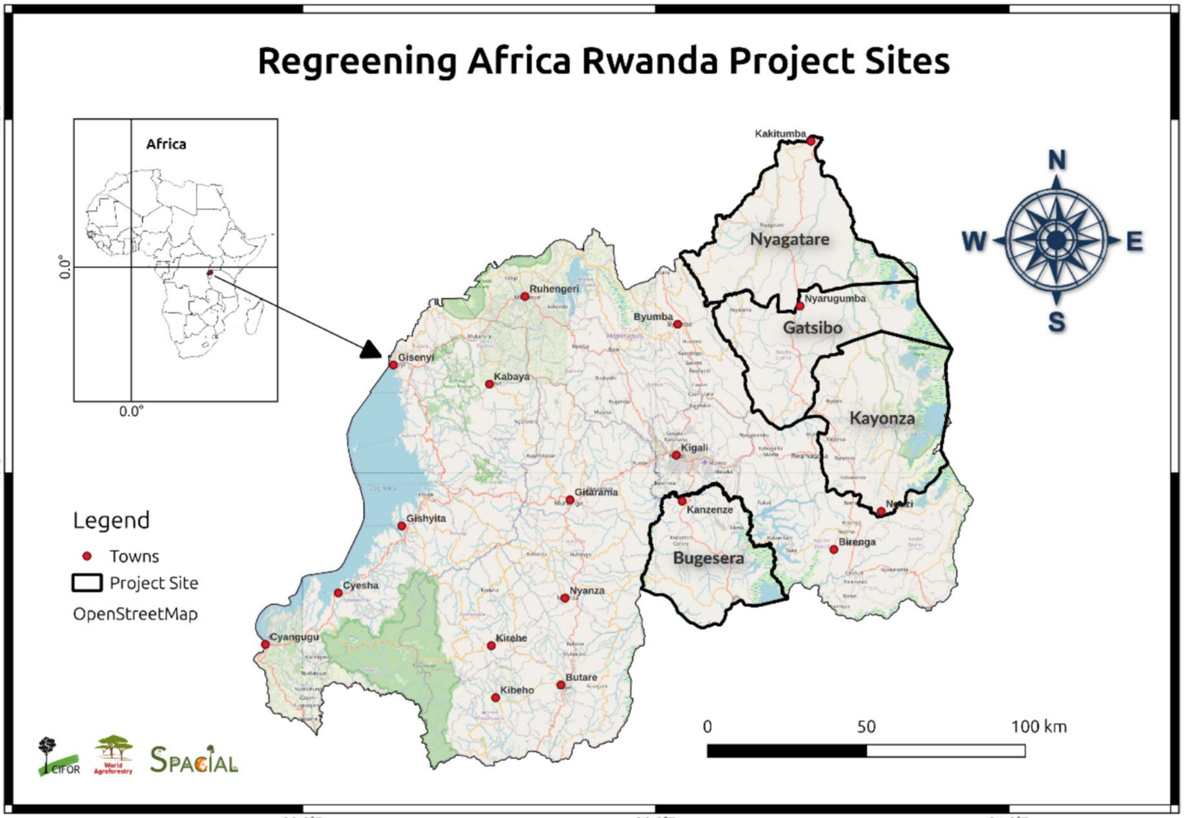


Fig. 1 Map showing the study areas. Source: World Agroforestry Spacial Laboratory

frequently experiences dry spells due to mismanagement of forests (Jonah et al. 2021; Ngango et al. 2023). The province is characterized by shrubland and wooded savannah covering over 200,000 hectares (MinEnv 2019). Natural forests cover less than 2000 hectares. Despite extensive national reforestation and conservation efforts, the province reported high deforestation rates, declining forest cover and low density in existing forests (MinEnv 2019). The province is notably the only rural area where the deforestation rate exceeded afforestation efforts, with significant forest losses recorded particularly in Kayonza (14%) and Nyagatare (16%) over a 10-year period (MinEnv 2019). This study area presents a suitable case for investigating agroforestry adoption because of the contextual issues highlighted above and previous investment in agroforestry interventions in the province (Ihli et al. 2022). This is crucial for informing future interventions and policy in similar agroecological zones.

Context, sampling and data collection

Data for this study was collected in sites where World Vision Rwanda implemented the RA program. RA was originally set up as a randomized control trial, and the sampling strategy and data collection were designed to align with that framework. However, non-compliance with the experimental protocol during program implementation rendered the experimental evaluation of the program unfeasible. This study therefore uses non-experimental approaches to investigate the impact of agroforestry interventions in the study area during the period coinciding with the implementation of RA, without necessarily attributing the impacts solely to RA.

Data were obtained from two surveys conducted by World Agroforestry (ICRAF) in the RA program sites in June 2018 and February 2022. Both surveys were conducted through face-to-face interviews. A team of trained enumerators interviewed respondents and entered data into the SurveyCTO© data collection tool on tablets and smartphones. Interviews were mainly done with either heads of households or their spouses. Prior to data collection, the survey tool was pretested and translated into the local language to ensure clarity and cultural relevance.

Stratified random sampling was used. From each of the four districts, eight cells[2] were randomly chosen, and from each cell, four villages were randomly selected. A random sample of 40 households was selected from the selected villages. The resultant sample was 1280 households, but only 1268 were interviewed at baseline, and 1132 re-interviewed at endline. This represents an 11% attrition rate. Attrition can be problematic if attritors are significantly different from non-attritors, in which case the sample would no longer represent the population from which it was drawn. To control any attrition bias, we apply the method suggested by Baulch and Quisumbing (2011). This entails conducting two probit regressions – one runs a full model with factors that might be associated with attrition (for example household demographic and socio-economic characteristics). The second model omits the variables that are found to be significantly associated with attrition in the first model. The ratio of predicted probabilities from the two regressions is then used to reweight the observations (Baulch and Quisumbing 2011). The resultant attrition weight is then incorporated in further analysis.

Data and description of treatment and outcome variables

The data collected includes household demographics and livelihood activities, social capital, land, livestock and asset ownership, farming practices, tree species, tree tenure and management, tree product use and earnings. The treatment variable, referred to as 'exposure' in this study is based on respondents' reports of receipt of any form of training, extension or advisory services related to the following topics in agroforestry: tree care and management, tree planting, FMNR, tree grafting, and nursery establishment and management. A household is considered to be exposed if an adult household member received any such training, extension services, or advisory sessions from any source during the study period. We decompose 'exposure' to further investigate heterogenous impacts by evaluating specific elements like the sources of exposure, the gender of the household members exposed and the topics of exposure. This approach is similar to that taken by Ragasa and Mazunda (2018), where the impact of specific measures of agricultural extension service delivery including the source, type and form of extension services delivery were examined to estimate their impact on farm productivity and food security in Malawi. In particular, we test the following: whether households that receive exposure from more than one source are more likely to adopt and practice agroforestry more intensively; whether the gender of household members exposed matters in tree planting adoption and practice, and whether the topics covered affect the outcomes. The impact of receiving tree seedlings among adopters is also analyzed to give a general picture of its effect on the intensity of practice.

Outcome variables

The primary objective of most agroforestry programs is to increase tree cover through tree planting. In this study, adoption is considered as binary, where a household is classified as having adopted if they planted at least one tree during the study period. Besides adoption, the intensity of practice is also important. Indicators of intensity include the number of trees, where they are planted and their diversity (Rudolf et al. 2020).

The intensity of agroforestry practice is estimated using the following indicators:

1. The change in the number of:

- Tree species
- Indigenous tree species
- Exotic tree species

2. The change in the number of trees:

- At the homestead
- In the main cropping field

[2] Cell: lowest administrative unit comprising several neighbouring villages where citizens can access basic government services.

Table 1 Comparison of baseline characteristics and outcome variables

	All HHs means	Exposed HHs means	Non-exposed HHs means	Difference
Household characteristics				
Gender of HH head, 1 = Female	0.25	0.20	0.27	−0.22*** (0.08)
Off-farm activities, 1 = Yes	0.34	0.36	0.32	0.12 (0.11)
Group membership, 1 = Yes	0.58	0.62	0.56	0.14 (0.10)
Age of household head	44.75	44.84	44.69	0.15 (0.89)
Household head level of education	3.98	4.34	3.76	0.58** (0.25)
Household size	4.66	4.78	4.59	0.19* (0.11)
Household had prior exposure, 1 = Yes	0.11	0.11	0.11	0.05 (0.09)
HH planted trees before baseline, 1 = Yes	0.18	0.22	0.16	0.19** (0.09)
Farm characteristics				
Approximate number of trees	22.25	24.02	21.20	2.82 (2.01)
Land size	0.43	0.48	0.40	0.08** (0.03)
Distance from administrative office	1.85	1.75	1.91	−0.17 (0.14)
Distance to nearest urban centre	6.80	6.56	6.95	−0.39 (0.52)
Outcome variables				
Household adopted tree planting	0.63	0.67	0.61	0.06** (0.03)
Change in number of trees—homestead	3.32	5.52	2.02	3.51*** (1.11)
Change in number of trees—main fields	6.70	11.23	4.03	7.20*** (2.02)
Change in number of tree species	1.09	1.29	0.97	0.32** (0.16)
Change in number of native species	−0.04	−0.04	−0.05	0.01 (0.07)
Change in number of exotic species	1.29	1.51	1.17	0.35** (0.14)
Observations	1132	420	712	1132

Standard errors in parentheses. $*p<0.1$, $**p<0.05$, $***p<0.01$

3. Number of trees planted over the study period

To reduce the high variation inherent in the tree numbers, the two variables in No. 2 were generated by following several steps. First, for each species, respondents self-reported the number of trees at the homestead and the main field by selecting one option from the ranges: 1 to 2; 3 to 5; 6 to 10; 11 to 20; 21 to 50; 51 to 100; 101 to 200; 201 to 500; over 500. For each species, the approximate number of trees is the midpoint of the range. The total number of trees either at the homestead or the main cropping field is obtained by adding up all the species estimates in each respective site (Hughes et al. 2022). For outcomes 1 and 2, the outcome variable is the difference between the baseline and endline values.

Descriptive statistics

We first examined if there were similarities in baseline characteristics between households exposed and those not exposed during the study period. Table 1 shows some imbalance in the mean values of some covariates, implying potential selection bias between exposed and non-exposed households. The average age of the household head was 44.75 years. In terms of the gender, 25% of household heads were female and 75% were male. The level of education was generally low with the mean overall number of years of education for household heads being almost 4 years. About 30% of household heads had no formal education. The average household size was 4.66 persons, but the number of people within households ranged from one to 14 members. More than half of the households – 58% had members who belonged to diverse social groups in the community, and 34% of the households engaged in at least one off-farm activity.

Key informant interviews revealed that several projects were implemented in the study area before 2018 both by government and non-governmental organizations. Most of these projects sought to address informational barriers to adoption and encourage tree planting among farmers. The effect of these other programs is estimated using two variables: prior exposure and prior practice. From the data, 11% of households were exposed to agroforestry practices before the baseline study. The percentage rose to 37% at the endline. Households had also practiced agroforestry before the baseline survey and 18% indicated that they had planted trees in the 12-month period prior to the baseline survey. This variable showed some significant difference between exposed and non-exposed households with the former having a significantly higher mean. This suggests that more exposed households were already engaged in tree planting activities beforehand. The percentage of households that adopted tree planting during the study period was 63%. Significant differences are evident in all outcomes except the change in the number of indigenous (native) tree species, indicating a potential positive association with exposure. However, due to potential selection bias we cannot draw any causal effect conclusions from this table.

Theoretical and empirical approaches

Lack of knowledge and skills have been identified as a major bottleneck to agroforestry adoption, which can be resolved through various means, including training and extension programs (Kpoviwanou et al. 2024). The human capital (HC) theory suggests that the productive capacity of people can be increased through education and skills training. In this study, exposure to agroforestry practices is an investment in human capital which enhances farmers' knowledge, technical capacities and decision-making abilities in agroforestry enabling them to better undertake agroforestry practices (Casey 2004). Through this, farmers can better understand benefits and optimize the integration of trees in farming systems, leading to better agroforestry adoption and intensified practice. However, noting that exposure in this study was not random, estimating the impact for exposed households in the absence of exposure poses a counterfactual challenge. Exposure may suffer from selection bias, with exposed farmers being systematically different from non-exposed ones. To address this counterfactual challenge, this study applies the HC theory within the potential outcomes framework.

A potential outcome is the possible outcome of a unit under a particular treatment state. There are two potential outcomes: $Y_i(1)$—if treated and $Y_i(0)$—if not treated. The treatment effect is the difference in potential outcomes if the unit received or did not receive treatment. The average treatment effect (ATE) which is the population mean of ($Y1$-$Y0$) and the average treatment effect on the treated (ATT), which is the mean of ($Y1$-$Y0$) among treated subjects can be estimated.

$$\text{Treatment effect} = Y_i(1) - Y_i(0) \tag{1}$$

But, for the same unit, both outcomes cannot be observed at the same time, meaning individual level effects in Eq. 1 cannot be estimated. We therefore estimate ATE as in Eq. 2.

$$ATE = E\left[Y_i(1)|D = 1\right] - E[Y_i(0)|D = 0] \tag{2}$$

where D is the treatment dummy.

However, simply comparing treated to untreated units in Eq. 2 may be biased because the two groups may differ in observable or unobservable ways. Furthermore, we want to know the effect of a specific treatment by estimating the causal impact on the treated subpopulation as shown in Eq. 3.

$$ATT = E\left[Y_i(1)|D = 1\right] - E[Y_i(0)|D = 1] \tag{3}$$

Since the second term in the equation, which is the potential outcome for treated households had they not been treated (the counterfactual) is not observed, a substitute for it must be found. The mean outcomes of non-treated units cannot be used in estimation due to potential selection biases. Selection bias implies that certain covariates that influence treatment selection may also correlate with the outcomes. Consequently, in the absence of treatment, the mean outcomes for the two groups could still exhibit differences. Experimental methods overcome this challenge by randomly assigning units to different treatment conditions. Randomization ensures similarity in both observative and unobservable characteristics between the two groups, except for treatment (Ferraro and Miranda 2014; Hughes et al. 2020). Although experimental impact evaluations are preferred, when impractical, non-experimental methods are employed (Wiik et al. 2019). To minimize confounding in non-experimental studies, differences between treatment groups that might influence the treatment status, or the outcome should be controlled. In the case of observable differences, various methods can be used, for example, propensity score matching (PSM), distance matching or inverse probability weighting (IPW). We adopt the IPW rather than PSM because it reduces bias by weighting the data using the estimated propensity scores.

IPW has two parts: (i) the selection model which uses a probit or logistic regression to estimate the probability of assignment to a treatment group (Kurz 2022). This is shown in Eq. 4 which generates propensity scores.

$$P(D = 1|X) = \frac{1}{1 + e^{-(\beta_0+\beta_1X_1+\beta_2X_2+\dots\dots\dots\dots+\beta_kX_k)}} \quad (4)$$

The inverse of the propensity scores is then calculated to obtain the inverse probability weights (Eqs. 5a and 5b) for both the exposed and non-exposed households.

$$\omega_{i1} = \frac{1}{P(D_i|X_i)} \text{for exposed households} \quad (5a)$$

$$\omega_{i0} = \frac{1}{1 - P(D_i|X_i)} \text{for non − exposed households} \quad (5b)$$

(ii) The weights account for the probability of treatment, therefore adjust for selection bias when analyzing the outcome.

The outcome model takes the regression form below:

$$Y = \alpha + \beta_0D + \beta_1X_1 + \beta_2X_2.\dots + \beta_kX_k + \varepsilon_i \quad (6)$$

where Y is the outcome, α is the intercept, β_0 is the treatment effect and β_{1-k} are effects of the covariates in the model and ε_i is the error term.

The ATE is then estimated using the weighted estimates in Eqs. 7a and b.

$$Y^*_{i1} = \omega_{i1} * Y_i, \text{for the treated group (D = 1)} \quad (7a)$$

$$Y^*_{i0} = \omega_{i0} * \left(1 - D_i\right) * Y_i, \text{ for the control group (D = 0)} \quad (7b)$$

Y^*_{i1} and Y^*_{i0} represent the weighted outcomes for the treated and non-treated groups, derived by multiplying the outcome, Y, by the corresponding weighted estimates. The ATE is then calculated as the difference between the expected values of weighted outcomes in (7a) and (7b).

IPW relies on various assumptions: (i) exchangeability – exposed and non-exposed households have similar covariate distributions. This assumption, however, does not apply in non-experimental cases (Shiba and Kawahara 2021); so, instead we seek to establish that conditional exchangeability holds. Conditional exchangeability assumes that exposed and non-exposed households share the distribution of a given vector of covariates – therefore we use the same covariates in the matching process and ensure balance between them before further analysis; (ii) positivity – there is a positive probability of households either being exposed or not being exposed, providing a basis for comparison and (iii) consistency which requires that the treatment is well defined (Shiba and Kawahara 2021; Chesnaye et al. 2022). Given the non-homogenous nature of the main treatment variable, this last assumption is addressed by separately analyzing various elements related to the treatment – which are more consistent, for example gender of exposed members and the topic of exposure.

This study uses a variation of IPW called augmented inverse probability weighting (AIPW), which adds an augmentation term to the outcome model to reduce variability and improve the estimation (Kurz 2022). When either the treatment or outcome models are correctly specified, AIPW produces efficient estimates. This property, known as 'doubly-robustness' makes AIPW more advantageous than IPW or regression methods (Kurz 2022). Furthermore, AIPW utilizes all observations in a dataset, effectively maintaining the sample size and making it preferable to PSM which sometimes eliminates some observations (Chesnaye et al. 2022).

To weight exposed and non-exposed households, we include factors like age, sex, and level of education of the household head and household size. Household participation in community level groups and participation in off-farm activities were also included. The size of land was included because it may influence the feasibility, scalability, and effectiveness of tree planting adoption. Another characteristic was the number of trees found in different land use areas before the baseline, which may affect household decision to adopt depending on whether they consider the trees to be sufficient

Table 2 Impact of exposure on adoption of tree planting

Comparison of households	Probability of adopting tree planting	Indicators of intensity					
		Change in # of tree species	Change in # of native trees	Change in # of exotic species	Change in # of trees homestead	Change in # of trees main field	# Of trees planted
Exposed after the baseline only vs never exposed	0.07** (0.03)	0.43*** (0.16)	0.05 (0.07)	0.40*** (0.14)	2.86** (1.13)	7.77*** (1.92)	4.45 (2.85)
Exposed before the baseline only vs never exposed	0.09* (0.05)	−0.48* (0.25)	−0.13 (0.12)	−0.28 (0.24)	−3.44** (1.55)	4.30* (2.56)	3.39 (4.20)
Exposed before and after the baseline vs never exposed	0.15** (0.06)	−0.15 (0.41)	−0.22 (0.14)	0.08 (0.39)	3.83 (2.44)	12.06** (4.77)	5.81 (5.95)
Exposed before the baseline vs exposed after baseline	−0.02 (0.06)	0.91*** (0.27)	0.18 (0.13)	0.68*** (0.25)	6.29*** (1.70)	3.47 (2.85)	1.06 (4.46)

Standard errors in parentheses, *$p<0.1$, **$p<0.05$, ***$p<0.01$

or not. Prior exposure and prior adoption of tree planting (before baseline) were included because they may determine household participation in current exposure programs. The distance to the cell office was included as a measure of access to administrative services and nearness to urban/peri-urban centres indicates proximity to information, markets and extension services. Baseline covariates were used in the weighting under the assumption that the variables were unaffected by the interventions that occurred later. Data analysis was done in Stata-17 and R.

Results

Treatment effects of exposure

Table 2 shows the ATE of exposure on tree planting adoption and on the intensity of tree planting practice. Comparisons were made between no exposure at all and (i) exposure before baseline, (ii) after baseline and (iii) both before and after baseline, as well as (iv) exposure after baseline versus exposure before baseline.

The results in Table 2 show a significant increase in the probability of adoption of 7% ($p=0.033$) among households that were exposed after the baseline compared to those entirely unexposed. Households that were only exposed before baseline had a 9% ($p=0.100$) increase in probability of adoption compared to those never exposed. The largest effect on adoption was 15%, ($p=0.011$), which was observed when households were exposed in both periods compared to those never exposed. The results also show that households exposed after baseline only reported a significant increase in tree species diversity (average of 0.43 species) compared to households that were never exposed. However, households exposed before the baseline only reported a significant decline of 0.48 in the number of species, compared to those never exposed. From the results, it is evident that the overall change in number of species was primarily driven by a change in the number of exotic species, rather than indigenous species. Exposure after the baseline also resulted in a significant increase in the number of trees at the homestead (2.86, $p=0.011$) and in the main cropping field (7.77, $p=0.001$). The last column shows the number of trees specifically planted in 2021. For this outcome, the impact of exposure was not statistically significant.

Treatment effects of exposure-related factors

Table 3 shows the impact of individual elements of exposure on the intensity of tree planting. Each

Table 3 Impact of exposure-related factors on the adoption and practice of tree planting

Comparisons	Probability of adopting tree planting	Indicators of intensity					
		Change in # of tree species	Change in # of native trees	Change in # of exotic species	Change in # of trees homestead	Change in # of trees main field	# Of trees planted
Topics of exposure							
Tree planting only vs none	0.10** (0.05)	0.61** (0.27)	0.03 (0.13)	0.53** (0.21)	0.28 (1.97)	7.64** (3.27)	1.56 (3.95)
Other topics vs none	0.07 (0.07)	0.44 (0.27)	0.13 (0.12)	0.32 (0.24)	3.63* (2.13)	5.87 (4.10)	1.63 (4.37)
Tree-planting vs other topics only	0.03 (0.08)	0.17 (0.37)	−0.10 (0.17)	0.21 (0.30)	−3.36 (2.81)	1.77 (5.09)	−0.07 (5.55)
Gender of household member exposed							
Male only vs none	0.20*** (0.04)	0.49** (0.24)	0.06 (0.11)	0.42** (0.20)	5.81*** (1.82)	10.11*** (2.67)	10.07*** (3.83)
Female only vs none	0.06 (0.05)	0.46 (0.30)	−0.02 (0.10)	0.46* (0.25)	3.17* (1.70)	−0.35 (3.09)	0.63 (4.48)
Both male and female vs none	−0.05 (0.04)	0.37 (0.23)	0.01 (0.11)	0.42** (0.19)	3.11* (1.59)	5.15* (2.66)	5.18 (3.88)
Male only vs female only	−0.13** (0.06)	−0.02 (0.36)	−0.08 (0.14)	0.04 (0.30)	−2.64 (2.33)	−10.46*** (3.85)	−9.44* (5.44)
Number of sources of exposure							
One source vs none	0.09** (0.04)	0.35* (0.20)	−0.00 (0.09)	0.36** (0.17)	3.50** (1.47)	7.01*** (2.21)	4.73 (3.42)
Many sources vs none	0.04 (0.04)	0.41** (0.19)	0.04 (0.09)	0.42** (0.16)	3.51** (1.37)	6.97*** (2.54)	3.87 (3.30)
One vs many sources	−0.05 (0.05)	0.06 (0.25)	0.04 (0.11)	0.05 (0.21)	0.01 (1.83)	−0.04 (3.07)	−0.86 (4.18)
Free seedling provision among adopters							
Received vs did not receive		0.53*** (0.17)	0.11 (0.08)	0.44*** (0.15)	3.31** (1.30)	7.62*** (2.10)	22.68*** (3.11)

Standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. # = number, (native species = indigenous species)

element was analyzed separately. Households that were specifically exposed to tree planting as a topic had a significant 10% increase in probability of adopting tree planting. Significant positive impacts were also observed on tree species diversity and number of exotic tree species which increased by 0.6 and 0.53, respectively. The number of trees on the main field significantly increased by 7.6, when farmers were specifically exposed to tree planting. Besides tree planting, other topics that farmers were exposed to included nursery management, FMNR, tree care and management, and grafting. These are collectively referred to as 'other topics'. Exposure to other topics only significantly affected the number of trees at the homestead by 3.6.

The impact of gender-related factors varied across outcomes. Exposing only male members was positive and significant for all outcomes, except the number of indigenous species. Exposing only male household members significantly increased the probability of adopting tree planting by 20%, while exposing only female household members did not significantly affect the probability of adopting tree planting. Exposing only female household members had significant positive impacts on the number of exotic species (0.46) and the number of trees at the homestead (3). Exposure of both male and female household members increased the number of trees at the homestead and the main field by 3 and 5, respectively and the number of exotic species by 0.42. Exposing male members only, as opposed to female members only, had a significant effect on the probability of adoption and led to a significant increase in the number of trees on the main field by 10 and the number of trees planted in 2021 by 9.

The findings also indicate that households exposed by single sources are more likely to adopt tree planting while there was no significant difference in other outcomes whether a household was exposed by one or multiple sources. The treatment effects in both cases were positive and significant for the overall diversity of tree species, diversity of exotic species, and the number of trees around homesteads and in the main fields.

Providing adopters with tree seedlings significantly increased species diversity by 0.53 ($p = 0.002$), with exotic species significantly increasing by 0.44 ($p = 0.002$). Seedling provision also significantly increased the number of trees planted during the study period by 23 and the number of trees around the homestead by 3.3 and in main fields by 7.6.

Robustness checks

The robustness of the AIPW model and the estimates were checked as follows: firstly, covariate balance was assessed by estimating standardized differences before and after weighting. After applying the AIPW, there was an improvement in the balance of covariates between exposed and non-exposed households. This is illustrated in Appendix 1, where the standardized differences of the variables tend towards a mean of zero and a standard deviation of one, indicating a more equitable distribution of covariates after weighting. Secondly, we confirmed that the overlap condition was satisfied using kernel density plots shown in Appendix 2. The illustration shows a significant area of overlap between the exposed and non-exposed households. The range of propensity scores (from just below 0.2 to 0.7) shows that there were no households close to 0 or 1, making the AIPW ideal. Finally, we compared the AIPW estimates with those from the traditional IPW analysis. The results are shown in Appendix 3. In many instances, the coefficients and standard errors of the AIPW estimates were quite close to the IPW estimates, providing reassurance that the results are robust.

Discussion

First, we find that exposure received in only one period – either before or after the baseline had modest effects on the probability of adopting tree planting. This suggests that, while important, simply exposing farmers to agroforestry practices may not be sufficient to boost tree planting. The probability of adopting was higher for households that received exposure both before and after the baseline. This implies that ongoing engagement with farmers may be required, as agroforestry demands extensive technical knowledge that goes beyond basic awareness creation (Pratiwi and Suzuki 2019; Pérez-Marulanda et al. 2025). Previous studies, for instance Wafula et al. (2016) found that enhancing the technical capacity of smallholders, though essential, was insufficient to spur adoption of conservation practices. Likewise, Rudolf et al. (2020) found that information provision alone led to only a few farmers planting indigenous trees in oil palm plantations in Indonesia. Providing new information to farmers can be beneficial; however, in some instances, it may have no impact (or have a negative effect) due to factors unrelated to the message itself (Mugizi 2025). For example, tree planting may be hindered by lack of planting materials, small land sizes or other factors. Therefore, other than exposure, programs should identify factors that may hinder adoption of agroforestry practices within their contexts and seek to address them. These factors could be environmental or socio-economic (Mwase et al. 2015; Wafula et al. 2016; Kiyani et al. 2017; Mgendi et al. 2021); intrinsic (Meijer et al. 2015b) or incentive-related (Ruseva et al. 2015).

Second, with respect to the intensity of tree planting practices, the study finds that exposure positively impacted the number and diversity of trees, with exposed households having more trees and tree species on farms and around homesteads. The diversity, however, was mostly due to an increase in exotic, rather than indigenous species. This could be attributed to various factors, for example, lack of indigenous tree seedlings or preference for exotic trees (Elias and Fabien 2024). It could also result from prior promotional efforts which emphasized the potential benefits of exotic trees at the expense of indigenous species. Deliberate efforts should be made to increase the diversity of indigenous species, through education and improved access to planting materials.

Third, gender analysis reveals that training male household members had a more significant impact on adoption and tree planting outcomes, for example the numbers of trees established in different land use areas, compared to training female members only.

The difference may be due to gender roles or complex socio-cultural structures generally existing in SSA (Niemann et al. 2024). The roles of men and women in agricultural activities differ across cultures (Catacutan and Naz 2015; Kiptot 2015). Traditional division of labour often confines women to more subsistence household roles limiting their participation in agroforestry and other climate change related decision-making (Niemann et al. 2024). Since men are traditionally the landowners, they also have tree ownership rights and typically make most decisions regarding land and trees (Kiptot 2015; Wafula et al. 2016; Niemann et al. 2024). Existing land and tree tenure systems deny women ownership rights (Kosoe and Darko 2022), particularly to high value timber trees like *Eucalyptus spp.* and *Grevillea robusta*. Consequently, the contribution of women may be undervalued despite their knowledge of conservation practices. In Malawi, although decision-making for most agricultural activities were made either by the husband or by the husband and wife together, decisions concerning agroforestry in the communities were mostly done by men (Meijer et al. 2015a). Since the community in our study area is patrilineal, this may explain the higher rates of adoption and more significant changes in tree numbers when male household members are exposed compared to when female members are exposed to agroforestry practices. And although not quite definitive from our results, the higher impact on outcomes that are observed when male household members are exposed, might suggest that men have more influence over land-use decisions in Rwanda, despite efforts to equalize ownership and rights through law (Bayisenge 2018). Besides, women are sometimes excluded from training and extension programs due to involvement in other household chores and nurturing children. Lack of access to such programs limits women's participation in agroforestry activities (Kosoe and Darko 2022), and may explain the lack of significance in the outcomes in this study. Agroforestry interventions should recognize and value the gender roles of both men and women, as women play a critical role in the early stages of tree establishment and management (Catacutan and Naz 2015; Kiptot 2015). Therefore, participation of both genders in agroforestry initiatives should be encouraged (Ajayi et al. 2016).

Another important factor was the number of sources of information, which included government extension officers, local administrative staff, lead farmers or non-governmental organization staff. Our findings reveal that exposure by either one or multiple agents was generally beneficial. In both cases, there were significant increases in the number and diversity of trees on farms. However, the marginal gains from an additional source beyond a single source were not significant. This suggests that a more focused approach using a single, well-designed information source may be sufficient and effective in reaching more people, rather than using multiple agents to reach a limited audience with the same information. This result agrees with findings from other studies, for example, Mwase et al. (2015) found that a pluralistic approach to extension provision might not really be beneficial as sometimes messages conflict and could confuse farmers. In the same vein, focusing on tree planting rather than other practices like grafting and FMNR is important in ensuring higher adoption of tree planting. Programs should therefore harmonize information provided to farmers and be very specific on the content (Mwase et al. 2015; Ragasa and Mazunda 2018).

Lastly, we investigated the impact of provision of tree seedlings on the intensity of tree planting among adopters. Previous studies have identified provision of seedlings as a major factor in agroforestry practice, with some linking low adoption rates to limited access to planting materials (Mwase et al. 2015; Ruseva et al. 2015; Jha et al. 2021; Tumuhe et al. 2021; Cyamweshi et al. 2023). Our findings corroborate these earlier studies showing that seedling provision significantly enhances number of trees and species diversity, although it does not notably impact the diversity of indigenous species. While the study context is different, Rudolf et al. (2020) found that when coupled with information provision, seedling provision led to more farmers planting indigenous trees in oil palm plantations in Indonesia. This implies that programs with higher capacity to provide tree seedlings will most likely attain higher adoption amongst farmers. However, such interventions should be well researched to establish how they can be promoted given cost implications and need for sustainability. Key informant interviews and field observations in the study area revealed that most nurseries only propagated exotic species, limiting access to indigenous species. Farmers were inclined to plant seedlings provided for free and did not take the initiative to plant other species. To increase species diversity, indigenous and multipurpose agroforestry trees should be made accessible and issues such as propagation of unsuitable or invasive tree species addressed (Ajayi et al. 2016; Veste et al. 2024). Attention should be paid to trees preferred by farmers and awareness created to improve understanding and acceptance of important but less-preferred trees.

As earlier indicated, diverse factors may hinder agroforestry practice. Previous studies highlighted lack of knowledge and skills, weak institutional support, access to land or secure land and tree tenure, high initial costs of adoption and access to planting materials as key barriers to agroforestry adoption (Kiyani et al. 2017; Kpoviwanou et al. 2024). Various recommendations can be drawn from the broader literature. To enhance adoption, policies to expand agroforestry programs to improve farmers' knowledge about sustainable practices, potential benefits and environmental impacts should be pursued. This would make farmers more independent in adopting technology and increasing long-term practice (Kpoviwanou et al. 2024; Kiyani et al. 2017). Strengthening land and tree tenure is required to encourage long-term investment in agroforestry practices (Veste et al. 2024; Tafere and Nigussie 2018). Historically, Rwanda's tree-planting initiatives have been driven by government policy, emphasizing the importance of aligning interventions with existing regulatory frameworks and ensuring better collaboration between formal and informal institutions (Binam et al. 2017; Veste et al. 2024). For instance, establishing tree nurseries and extension support through existing institutions like farmer cooperatives or groups may provide an avenue through which exposure to agroforestry practices and access to planting materials can be enhanced.

Conclusion and recommendations

Agroforestry programs are critical in enhancing adoption of land restoration practices by exposing farmers to various technologies through training, advisory services or technical support. This study examined whether exposure increased the likelihood of adopting tree planting and enhancing the diversity and number of trees in different land use areas among smallholder farmers in Eastern Rwanda. The study used panel data and applied the AIPW method to estimate impact while addressing selection bias. Beyond the often-analyzed binary access to training/extension services variable, this study decomposed 'exposure' to investigate three factors: gender of exposed household members, specific topic of exposure and sources of exposure enabling a more nuanced analysis of how they influence outcomes and providing insights for designing future agroforestry interventions. We conclude that although exposure is important, it is not sufficient to boost adoption of agroforestry practices. We suggest continuous engagement with farmers to sustain adoption. Challenges that hinder adoption and intensive practice in particular contexts should be identified and addressed. Exposure to men in households had more significant effects compared to exposure to women only. Given women's critical role in rural production systems, both genders should be equitably involved in agroforestry initiatives. For more conclusive insights on gender dynamics, future research should consider the nature of the treatment in more detail, for example, if interventions to men and women provided similar content and targeted similar technologies. Another finding was that it was not necessary to have multiple sources of information as the marginal gains from an additional source of information were not significant, and that one source of information may just be effective if well-structured and targeted.

This study acknowledges some limitations. First, while the proportion of households exposed in our sample accurately reflects exposure levels in the population, the overall low exposure rates may have limited our ability to detect significant effects. Future research could benefit from interventions with higher saturation or more intensive exposure to more robustly assess their impacts. Second, while our findings reveal a significant correlation between seedlings provision and intensity of tree planting, the question about the source of tree seedlings, whether acquired freely or purchased, was only posed to adopting households. This oversight potentially introduces bias, by excluding households that may have received seedlings but chose not to plant them. Therefore, the implications drawn from seedling provision must be cautiously interpreted. Future research should address this gap to provide a more comprehensive understanding of the relationship between free tree seedling distribution and subsequent tree planting practices. Nonetheless, this result shows the effect of seedling provision on important outcomes among adopters, for instance, farmers tended to grow only the tree species available in nurseries or offered to them, hence attention should be paid to the kind of tree species raised in nurseries. Future research should also refine the methodologies used, for example use difference-in-difference analysis for panel data and explore the complexities of agroforestry interventions by investigating different elements that might be critical including: the period covered by the intervention, the form of exposure, the content and delivery method of messages and the frequency of exposure. The long-term effects of agroforestry exposure programs should also be evaluated in future studies to gauge program efficacy and to better understand if behavioural changes have been sustained over time.

Author contribution Author contribution: HK: conceptualization, methodology, analysis, writing main draft, paper revision. DJ: methodology, analysis, writing main draft. TW: conceptualization, methodology, writing main draft, paper revision. KH: conceptualization, methodology, writing main draft. STK: writing and reviewing draft. All authors reviewed the manuscript.

Funding Open access funding provided by University of Pretoria.

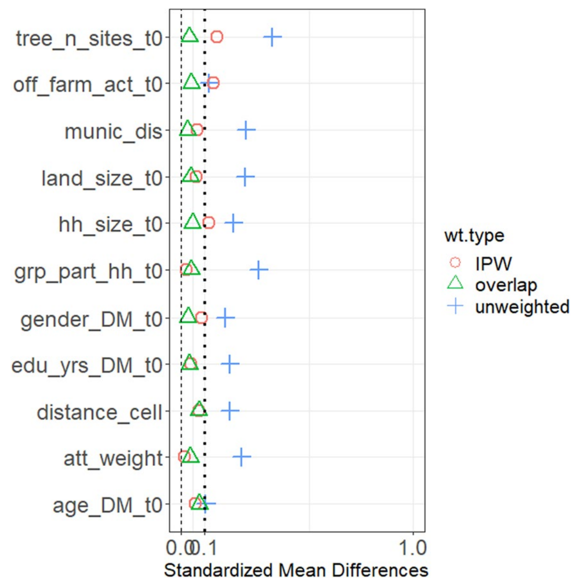
Data availability Survey data used in this study will be made available upon reasonable request to the corresponding author.

Declarations

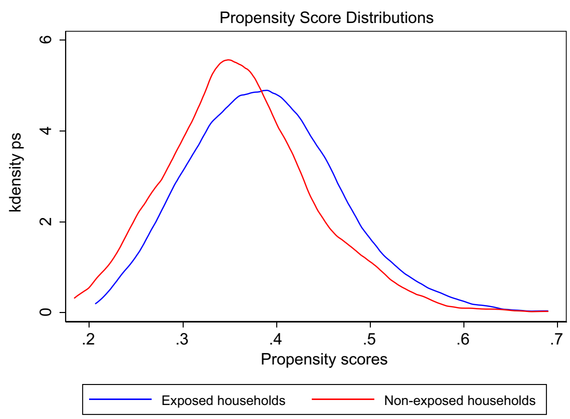
Conflict of interest The authors have no relevant financial or non-financial interests to disclose. The authors have no conflicts of interest to declare that are relevant to the content of this article. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. The authors have no financial or proprietary interests in any material discussed in this article.

Appendixes

Appendix 1: Standardized mean differences for the treatment variable



Appendix 2: K-density distributions of propensity scores



Appendix 3: Treatment effects of exposure-related factors on the adoption and practice of tree planting using IPW

Comparisons	Probability of adopting tree planting	Indicators of intensity					
		Change in # of tree species	Change in # of native trees	Change in # of exotic species	Change in # of trees homestead	Change in # of trees main field	#Of trees planted
Topics of exposure							
Tree planting only vs none	0.10** (0.05)	0.60** (0.27)	0.04 (0.13)	0.50** (0.21)	0.21 (1.94)	7.88** (3.17)	1.53 (3.86)
Other topics vs none	0.07 (0.06)	0.32 (0.28)	0.10 (0.12)	0.23 (0.25)	4.43** (2.17)	4.16 (3.73)	3.63 (5.25)
Tree-planting vs other topics only	0.03 (0.07)	0.28 (0.38)	−0.06 (0.17)	0.27 (0.32)	−4.22 (2.83)	3.72 (4.74)	−2.09 (6.21)
Male only vs none	0.19*** (0.036)	0.44* (0.24)	0.05 (0.11)	0.39* (0.20)	5.95*** (1.85)	9.70*** (2.70)	9.70*** (3.76)
Gender of household member exposed							
Female only vs none	0.06 (0.05)	0.51* (0.30)	−0.01 (0.11)	0.50* (0.26)	3.34** (1.66)	0.46 (3.39)	0.46 (4.52)
Both male and female vs none	−0.05 (0.04)	0.39* (0.24)	0.02 (0.11)	0.44** (0.19)	2.93* (1.56)	5.72** (2.69)	4.87 (4.23)
Male only vs female only	−0.13** (0.06)	0.07 (0.37)	−0.05 (0.14)	0.11 (0.31)	−2.61* (2.33)	−9.24** (4.11)	−9.24* (5.42)
Number of sources of exposure							
One source vs none	0.09** (0.04)	0.36* (0.20)	−0.00 (0.09)	0.37** (0.17)	3.71** (1.47)	7.45*** (2.19)	4.65 (3.41)
Many sources vs none	0.04 (0.04)	0.42** (0.19)	0.03 (0.09)	0.44*** (0.16)	3.62*** (1.39)	6.21** (2.52)	5.13 (3.35)
One vs many sources	−0.04 (0.05)	0.06 (0.25)	0.03 (0.12)	0.07 (0.21)	−0.09 (1.83)	−1.24 (3.04)	0.49 (4.21)
Free seedling provision among adopters							
Received vs did not receive free seedlings		0.53*** (0.17)	0.11 (0.08)	0.44*** (0.15)	3.40** (1.27)	7.94*** (2.08)	23.07*** (3.10)

References

Ajayi O, Akinnifesi F, Ajayi A (2016) How by-laws and collective action influence farmers' adoption of agroforestry and natural resource management technologies: lessons from Zambia. Forests, Trees Livelihoods 25(2):102–113

Asrat P, Simane B (2017) Household-and plot-level impacts of sustainable land management practices in the face of climate variability and change: empirical evidence from Dabus Sub-basin, Blue Nile River, Ethiopia. Agric Food Secur 6(1):1–12

Baulch B, Quisumbing A (2011) Testing and adjusting for attrition in household panel data. CPRC Toolkit Note 1(1):1–12

Bayisenge J (2018) From male to joint land ownership: women's experiences of the land tenure reform programme in Rwanda. J Agrar Chang 18(3):588–605

Baylis K, Honey-Rosés J, Börner J, Corbera E, Ezzine-de-Blas D, Ferraro PJ, Lapeyre R, Persson UM, Pfaff A, Wunder S (2016) Mainstreaming impact evaluation in nature conservation. Conserv Lett 9(1):58–64

Binam JN, Place F, Djalal AA, Kalinganire A (2017) Effects of local institutions on the adoption of agroforestry innovations: evidence of farmer managed natural regeneration and its implications for rural livelihoods in the Sahel. Agric Food Econ 5(1):1–28

Buyinza J, Nuberg IK, Muthuri CW, Denton MD (2020) Psychological factors influencing farmers' intention to adopt agroforestry: a structural equation modeling approach. J Sustain for 39(8):854–865

Cameron DB, Mishra A, Brown AN (2016) The growth of impact evaluation for international development: How much have we learned? J Dev Eff 8(1):1–21

Casey JF (2004) Agroforestry adoption in Mexico: using Keynes to better understand farmer decision-making. J Post Keynesian Econ 26(3):505–521

Castle SE, Miller DC, Ordonez PJ, Baylis K, Hughes K (2021) The impacts of agroforestry interventions on agricultural productivity, ecosystem services, and human well-being in low-and middle-income countries: a systematic review. Campbell Syst Rev 17(2):1–52

Catacutan D, Naz F (2015) Gender roles, decision-making and challenges to agroforestry adoption in Northwest Vietnam. Int for Rev 17(4):22–32

Chesnaye NC, Stel VS, Tripepi G, Dekker FW, Fu EL, Zoccali C, Jager KJ (2022) An introduction to inverse probability of treatment weighting in observational research. Clin Kidney J 15(1):14–20

Cornelius JP, Miccolis A (2018) Can market-based agroforestry germplasm supply systems meet the needs of forest landscape restoration? New for 49(4):457–469

Coulibaly JY, Chiputwa B, Nakelse T, Kundhlande G (2017) Adoption of agroforestry and the impact on household food security among farmers in Malawi. Agric Syst 155:52–69

Cyamweshi RA, Kuyah S, Mukuralinda A, Ngango J, Mbaraka SR, Manirere JD, Muthuri WC (2023) Farming with trees for soil fertility, moisture retention and crop productivity improvement: perceptions from farmers in rwanda. Small-Scale for 22(4):649–667. https://doi.org/10.1007/s11842-023-09547-x

Danquah M, Amankwah-Amoah J (2017) Assessing the relationships between human capital, innovation and technology adoption: evidence from sub-Saharan Africa. Technol Forecast Soc Chang 122:24–33

Elias M, Fabien R (2024) Perception and knowledge of local community on the use of indigenous tree species for ecosystem restoration in Gasabo district, Rwanda. Rwanda J Eng, Sci, Technol Environ 6(1):1–19

Ferraro PJ, Miranda JJ (2014) The performance of non-experimental designs in the evaluation of environmental programs: a design-replication study using a large-scale randomized experiment as a benchmark. J Econ Behav Organ 107:344–365

Hillbrand A, Borelli S, Conigliaro M, Olivier E (2017) Agroforestry for landscape restoration: exploring the potential of agroforestry to enhance the sustainability and resilience of degraded landscapes.

Hughes K, Morgan S, Baylis K, Oduol J, Smith-Dumont E, Vågen T-G, Kegode H (2020) Assessing the downstream socioeconomic impacts of agroforestry in Kenya. World Dev 128:104835

Hughes K, Oduol JBA, Kegode H, Kimaiyo J, Mausch K (2022) Experimental evidence from a fodder shrub promotional effort among dairy farmers in Uganda. J Dev Eff 15(4):373–388

Ihli H, Seegers R, Winter E, Chiputwa B, Gassner A (2022) Preferences for tree fruit market attributes among smallholder farmers in Eastern Rwanda. Agric Econ 53(1):5–21

Jha S, Kaechele H, Sieber S (2021) Factors influencing the adoption of agroforestry by smallholder farmer households in Tanzania: case studies from Morogoro and Dodoma. Land Use Policy 103:105308

Jonah K, Wen W, Shahid S, Ali MA, Bilal M, Habtemicheal BA, Iyakaremye V, Qiu Z, Almazroui M, Wang Y (2021) Spatiotemporal variability of rainfall trends and influencing factors in Rwanda. J Atmos Solar Terr Phys 219:105631

Kiptot E (2015) Gender roles, responsibilities, and spaces: implications for agroforestry research and development in Africa. Int for Rev 17(4):11–21

Kiyani P, Andoh J, Lee Y, Lee DK (2017) Benefits and challenges of agroforestry adoption: a case of Musebeya sector, Nyamagabe District in southern province of Rwanda. For Sci Technol 13(4):174–180

Kosoe EA, Darko FD (2022) Socioeconomic and cultural influence on women's participation in agroforestry in Jaman South, Ghana. In: Socioeconomic Shocks and Africa's Development Agenda. Routledge, pp 9–26

Kpoviwanou MRJH, Sourou BKN, OUINSAVI CAN (2024) Challenges in adoption and wide use of agroforestry technologies in Africa and pathways for improvement: a systematic review. Trees, Forests and People:100642

Kulindwa YJ (2016) Key factors that influence households' tree planting behaviour. Nat Res Forum 40(1–2):37–50

Kulindwa YJ, Ahlgren EO (2021) Households and tree-planting for wood energy production: Do perceptions matter? Forest Policy Econ 130:102528

Kurz CF (2022) Augmented inverse probability weighting and the double robustness property. Med Decis Making 42(2):156–167

Leßmeister A, Heubach K, Lykke AM, Thiombiano A, Wittig R, Hahn K (2018) The contribution of non-timber forest products (NTFPs) to rural household revenues in two villages in south-eastern Burkina Faso. Agrofor Syst 92:139–155

Malan M, Berkhout E, Duchoslav J, Voors M, Van Der Esch S (2024) Socioeconomic impacts of land restoration in agriculture: a systematic review. Q Open 4(2):1–17

Meijer SS, Catacutan D, Ajayi OC, Sileshi GW, Nieuwenhuis M (2015a) The role of knowledge, attitudes and perceptions in the uptake of agricultural and agroforestry innovations among smallholder farmers in sub-Saharan Africa. Int J Agric Sustain 13(1):40–54

Meijer SS, Catacutan D, Sileshi GW, Nieuwenhuis M (2015b) Tree planting by smallholder farmers in Malawi: using the theory of planned behaviour to examine the relationship between attitudes and behaviour. J Environ Psychol 43:1–12. https://doi.org/10.1016/j.jenvp.2015.05.008

Mgendi G, Mao S, Qiao F (2021) Is a training program sufficient to improve the smallholder farmers' productivity in Africa? empirical evidence from a Chinese agricultural technology demonstration center in Tanzania. Sustainability 13(3):1527

Miller DC, Ordoñez PJ, Brown SE, Forrest S, Nava NJ, Hughes K, Baylis K (2020) The impacts of agroforestry on agricultural productivity, ecosystem services, and human well-being in low-and middle-income countries: an evidence and gap map. Campbell Syst Rev. https://doi.org/10.1002/cl2.1066

MinEnv (2019) Rwanda forest cover mapping. Ministry of environment, Kigali

Mugizi FM (2025) Extension advice, agricultural productivity, and food security in Tanzania. Food Energy Secur 14(1):e70047

Muthee K, Duguma L, Majale C, Mucheru-Muna M, Wainaina P, Minang P (2022) A quantitative appraisal of selected agroforestry studies in the Sub-Saharan Africa. SSRN Electron J. https://doi.org/10.2139/ssrn.4067952

Mwase W, Sefasi A, Njoloma J, Nyoka BI, Manduwa D, Nyaika J (2015) Factors affecting adoption of agroforestry and evergreen agriculture in Southern Africa. Environ Nat Resour Res 5(2):148

Ngango J, Musabanganji E, Maniriho A, Nkikabahizi F, Mukamuhire A (2023) Examining the adoption of agroforestry in Southern Rwanda: a double hurdle approach. For Sci Technol 19(4):260–267

Niemann J, El-Mahdi M, Samuelsen H, Tersbøl BP (2024) Gender relations and decision-making on climate change adaptation in rural East African households: a qualitative systematic review. PLOS Climate 3(1):e0000279

NISR (2023) Fifth rwanda population and housing census, 2022. Main indicators report. national institute of statistics of rwanda, Kigali, Rwanda

Nkonya E, Mirzabaev A, Von Braun J (2016) Economics of land degradation and improvement: a global assessment for sustainable development. Springer Nature, Cham

Ntawuruhunga D, Ngowi EE, Mangi HO, Salanga RJ, Shikuku KM (2023) Climate-smart agroforestry systems and practices: a systematic review of what works, what doesn't work, and why. Forest Policy Econ 150:102937

Pantera A, Mosquera-Losada M, Herzog F, Den Herder M (2021) Agroforestry and the environment. Agrofor Syst 95(5):767–774

Pérez-Marulanda L, Jepsen MR, Castro-Nunez A (2025) Boosting the adoption of sustainable land-use systems for achieving Colombian land-based climate action and peacebuilding goals. World Dev 188:106888

Pratiwi A, Suzuki A (2019) Reducing agricultural income vulnerabilities through agroforestry training: evidence from a randomised field experiment in Indonesia. Bull Indones Econ Stud 55(1):83–116

Pratiwi A, Suzuki A (2020) Does training location matter? Evidence from a randomized field experiment in rural Indonesia. Agric Food Econ 8:1–23

Ragasa C, Mazunda J (2018) The impact of agricultural extension services in the context of a heavily subsidized input system: the case of Malawi. World Dev 105:25–47

Rudolf K, Romero M, Asnawi R, Irawan B, Wollni M (2020) Effects of information and seedling provision on tree planting and survival in smallholder oil palm plantations. J Environ Econ Manag 104:102361

Ruseva TB, Evans TP, Fischer BC (2015) Can incentives make a difference? Assessing the effects of policy tools for encouraging tree-planting on private lands. J Environ Manage 155:162–170

Shiba K, Kawahara T (2021) Using propensity scores for causal inference: pitfalls and tips. J Epidemiol 31(8):457–463

Syano NM, Nyangito MM, Wasonga OV, Kironchi G (2022) Agroforestry practices and factors influencing their adoption by communities in the drylands of Eastern Kenya. Agrofor Syst 96(8):1225–1235

Tafere SM, Nigussie ZA (2018) The adoption of introduced agroforestry innovations: determinants of a high adoption rate: a case-study from Ethiopia. Forests, Trees Livelihoods 27(3):175–194

Tumuhe CL, Nyamaizi S, Gawaya G, Kiguli J (2021) Incentives influencing tree planting in the Albertine rift region, Uganda. J Sustain for 40(6):558–572

UNCCD (2014) Land degradation neutrality: resilience at local, national and regional levels. UNCCD Secretariat Bonn,

Veste M, Sheppard JP, Abdulai I, Ayisi KK, Borrass L, Chirwa PW, Funk R, Kapinga K, Morhart C, Mwale SE (2024) The need for sustainable agricultural land-use systems: Benefits from integrated agroforestry systems. In: sustainability of Southern African ecosystems under global change: science for management and policy interventions. Springer, pp 587–623

Wafula L, Oduol J, Oluoch-Kosura W, Muriuki J, Okello J, Mowo J (2016) Does strengthening technical capacity of smallholder farmers enhance adoption of conservation practices? The case of conservation agriculture with trees in Kenya. Agrofor Syst 90:1045–1059

Wawire AW, Csorba Á, Tóth JA, Michéli E, Szalai M, Mutuma E, Kovács E (2021) Soil fertility management among smallholder farmers in Mount Kenya East region. Heliyon 7 (3)

Wiik E, d'Annunzio R, Pynegar E, Crespo D, Asquith N, Jones JP (2019) Experimental evaluation of the impact of a payment for environmental services program on deforestation. Conserv Sci Pract 1(2):e8

Wossen T, Abdoulaye T, Alene A, Haile MG, Feleke S, Olanrewaju A, Manyong V (2017) Impacts of extension access and cooperative membership on technology adoption and household welfare. J Rural Stud 54:223–233

Zaca FN, Ngidi MSC, Chipfupa U, Ojo TO, Managa LR (2023) Factors influencing the uptake of agroforestry practices among rural households: empirical evidence from the KwaZulu-Natal province. South Afr for 14(10):2056